Analysis on Romance Movies with the IMDb dataset

PIC 16 Final Project

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OUR PROCESS

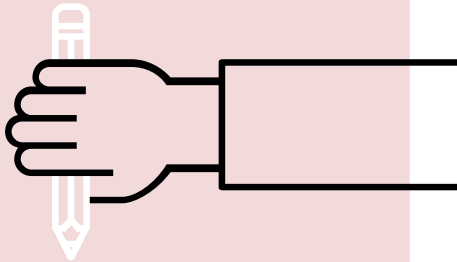
I:
Trend Analysis
Years
&
Popularity

II:
Visualization
Romance Movies
&
Production
Countries

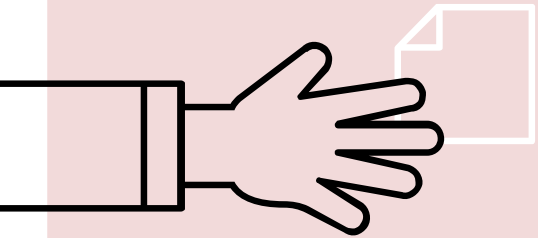
III:
Classification
Romance Movies
&
Movie Quality

Idea

- Use a **subset** of data -> obtain specific conclusions
- Explore the **internal pattern** of romance movie production
- **Generalize** to more romance movies



I. Popularity Over Time

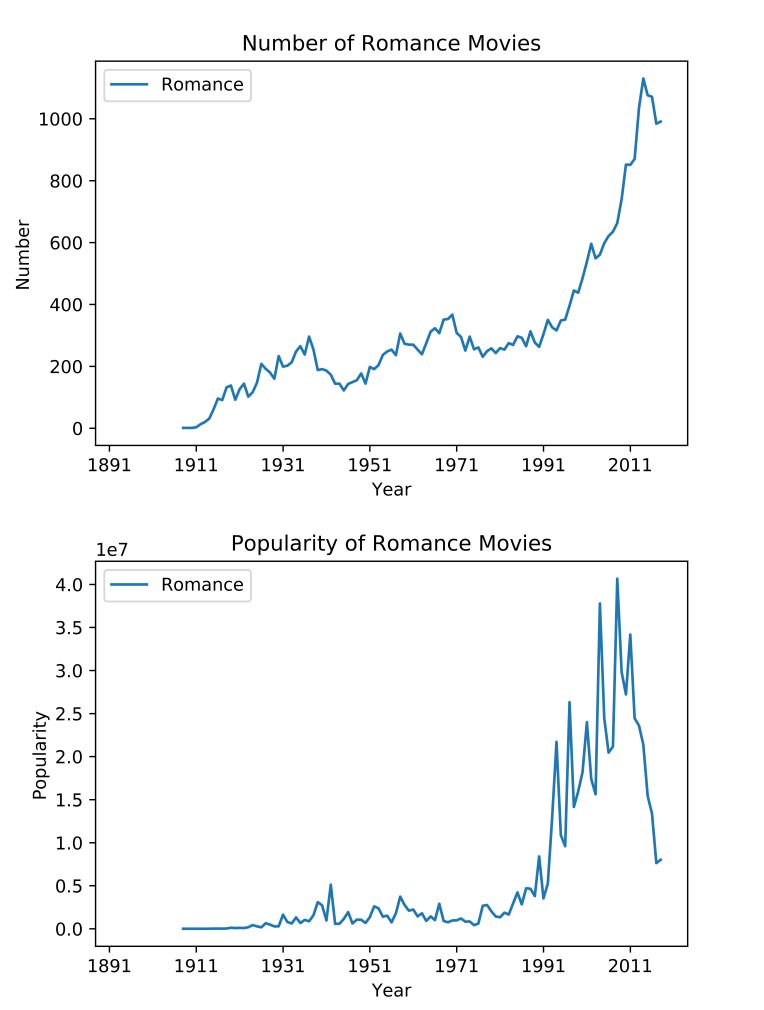


Basic Data Cleaning

- **Original Data**: (downloaded at https://datasets.imdbws.com)
  - title.basics.tsv.gz (tconst, titleType, startYear, genres)
  - title.ratings.tsv.gz (tconst, averageRating, numVotes)
  - title.akas.tsv.gz
- Use **pandas**.DataFrame.apply and **filter functions** to find all the movies before 2019
- **Merge** with ratings, and **compute popularity** (averageRating * numVotes) for each movie
- Basics: 5687200 x 9 Ratings: 914862 x 3
- Movies: 450481 x 4 (tconst, startYear, genres, Popularity)

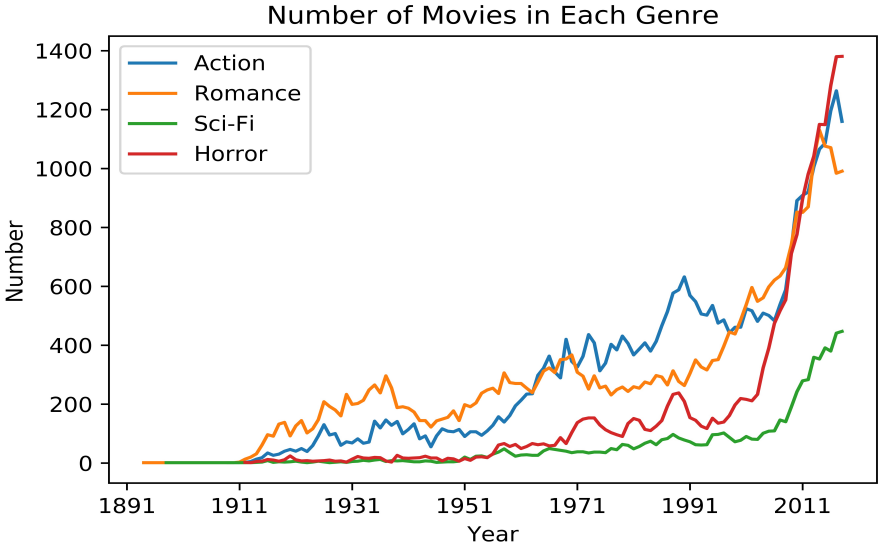
Data Aggregation

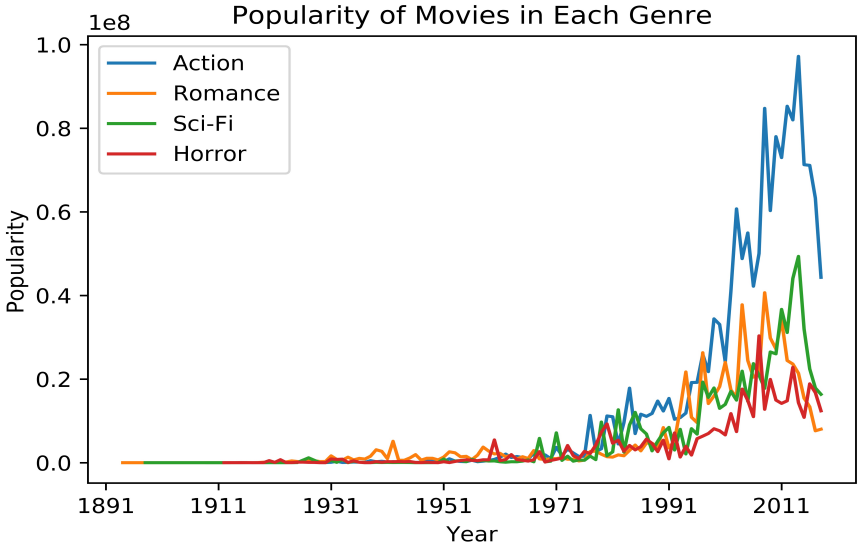
- Goal: IMDb **user preference** on movie genres over time
- Use count() and sum() in **pandas.DataFrame.groupby** on **'startYear'**
- Use df.apply and filter functions to find specific genre
- **Two Measurements:** total number and popularity



Genre Comparison

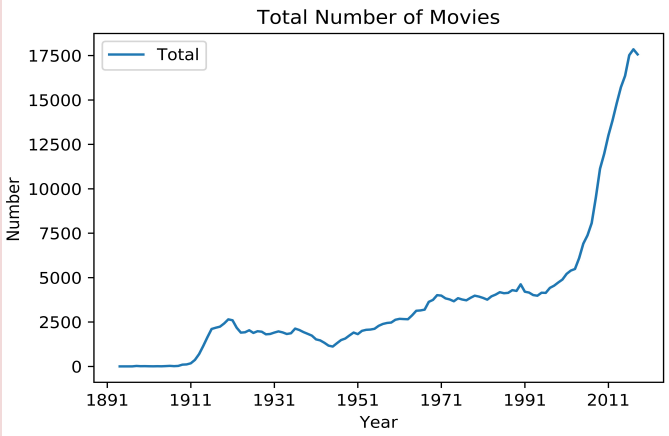
- Four genres: Romance, Action, Science Fiction, Horror

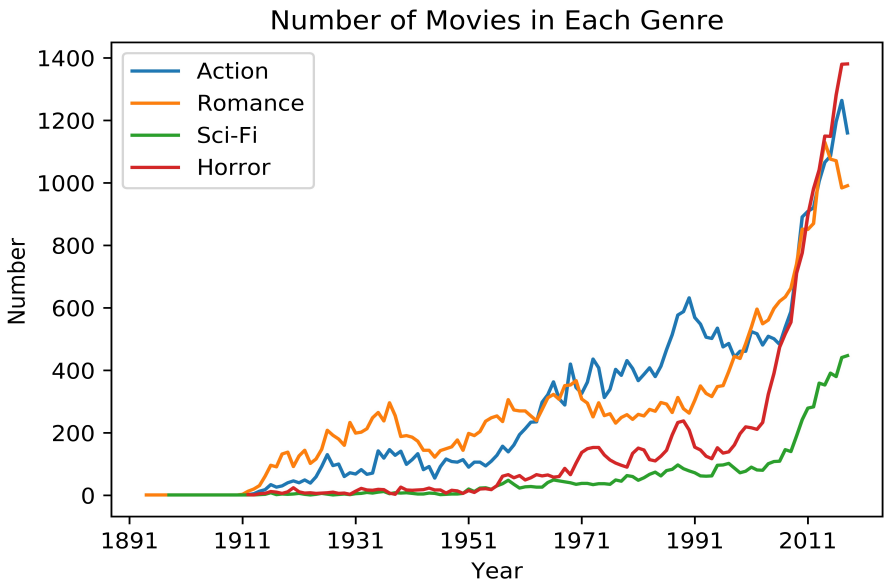


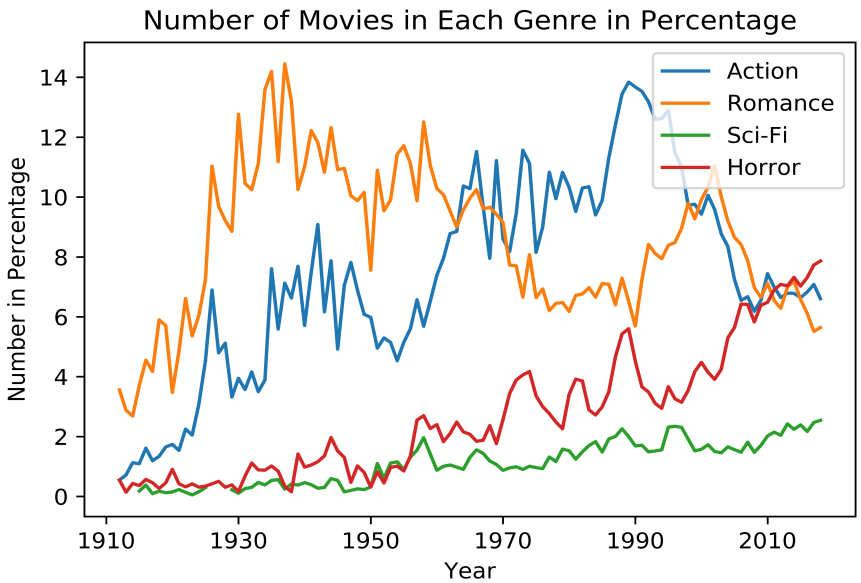


Regularization

- **Problem**: The movie industry is growing itself
- **Solution**: Take percentage on movie numbers (# of movies in a genre / # of movies)

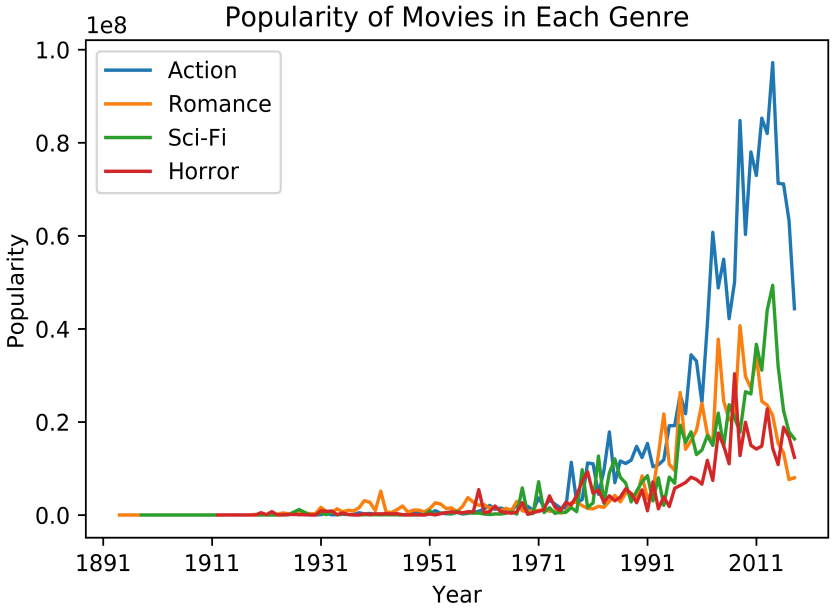


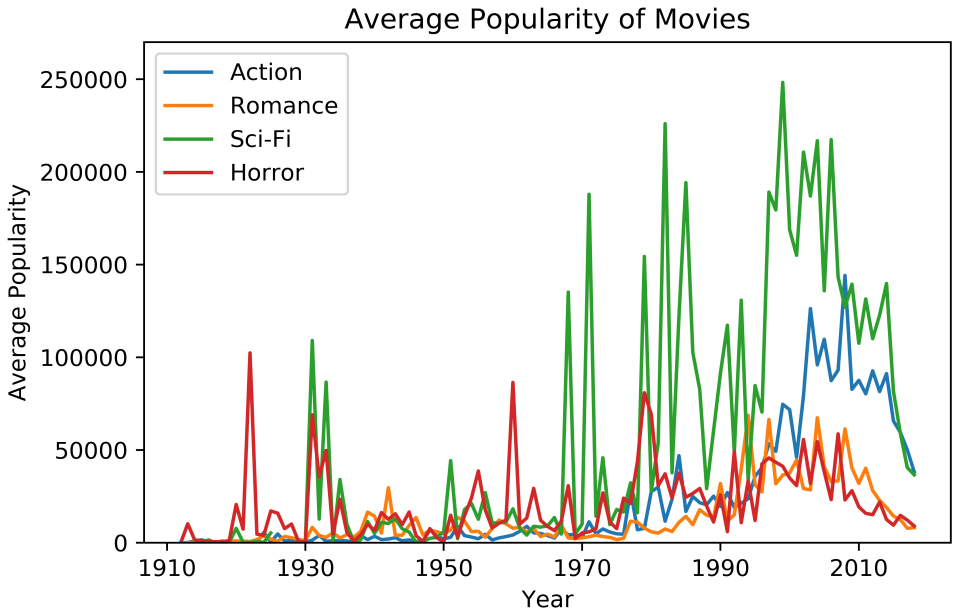




Regularization

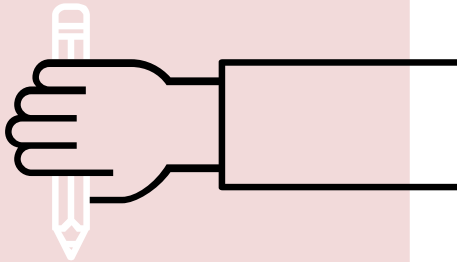
- **Problem**: More movies, higher popularity
- **Solution**: Take average (genre popularity / # of movies in that genre)



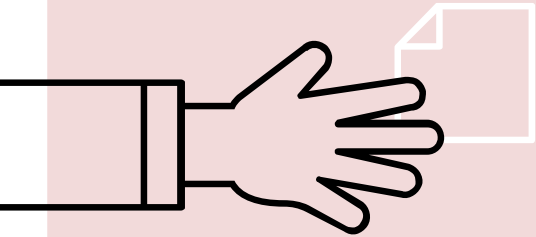


Findings

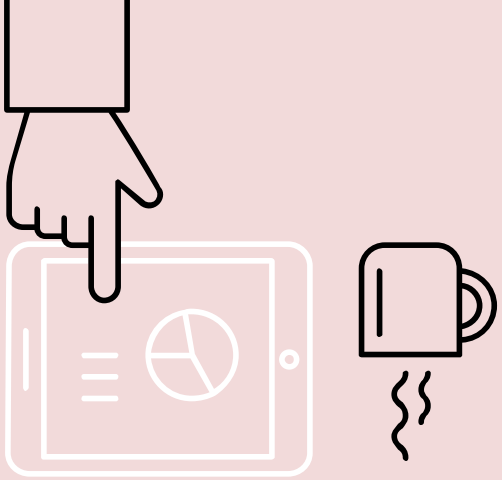
- Romance movies were more **popular back in the old days**
- People **switch their tastes** to action movies
- Producers **makes less** and less romance and action movies in recent ten years
- Producers starts to make more horror movies. However, they are not as appreciated as other genres.
- Producers make less science fiction movies, but people love the existing ones



II. Relationship Between Romance Movies and Producing Countries



Data Manipulation



Datasets

- title.akas.tsv: includes **foreign names** of every movie
- title.basics.tsv: includes **genres** of each movie
- Country_loc.tsv: contains **abbreviation, longitudes and latitudes** of each country

Key Process

```
def filter_genre(row):
    if type(row["genres"]) is str and type(row["titleType"]) is str and "Romance" in row["genres"].split(",") and row["titleType"]=="movie":
        return True
    return False
```

- Movies: **romance** + could be classified as Movies
- Countries: Standard Alpha-2 Code + appeared in movie dataset

Data Manipulation

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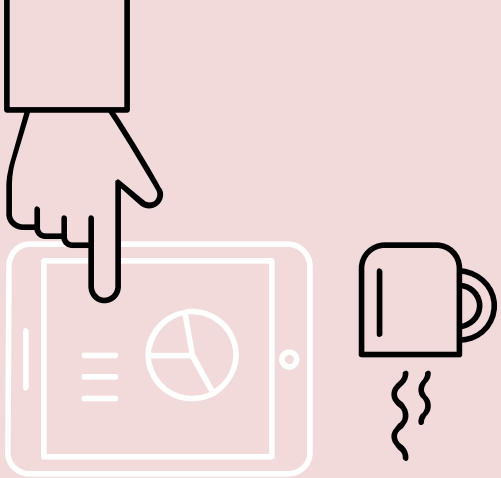

Data Manipulation

- The **number of title versions** of each movie indicates the **number of exported countries**
- Collecting all movies from the same original country to derive the relationships among countries in the world

Results

No. of Romance Movies Export Illustration

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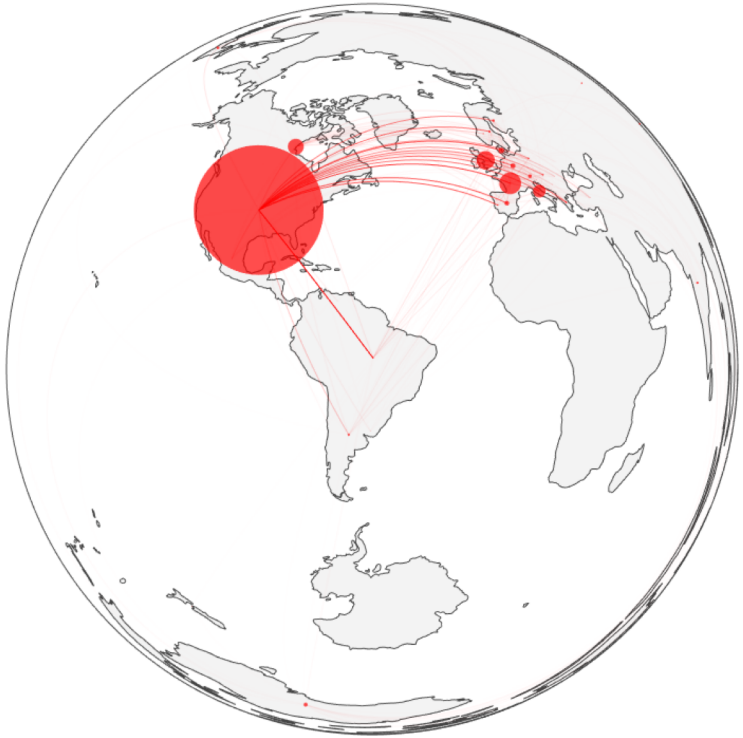
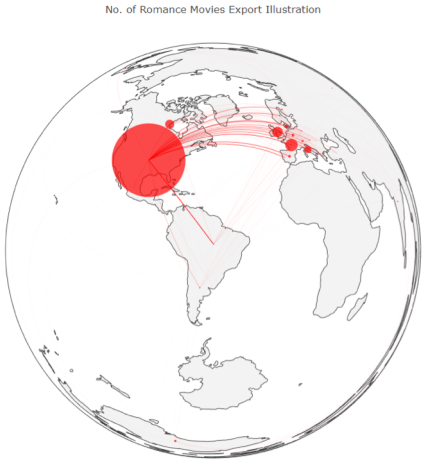




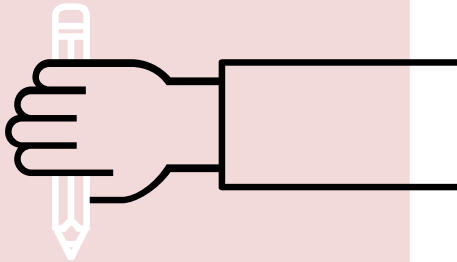
exports.html

Observations

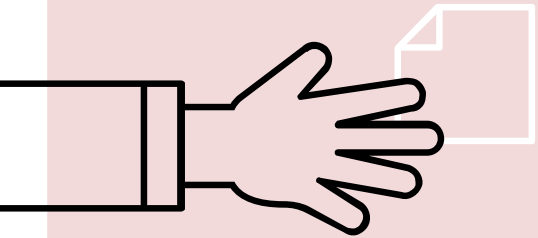
1. **Highest exporting countries** in volume:
   - U.S.
   - France
   - U.K.
   - Canada
   - Italy
2. **Dense in the Western world**, while minimal exports in the rest of the globe.

Interpretations

1. **Developed countries** produce more movies in general.
2. The concept of "Romance and Love" has **higher cultural uniformity in the Western World**, while numerous cultural implications of "love" in the East might result in few exports of their romance movies.
3. There is an enormous **gap** between Eastern and Western **understanding** of "Romance".



III. Binary Classification of Romance Movies Based on Average Rating

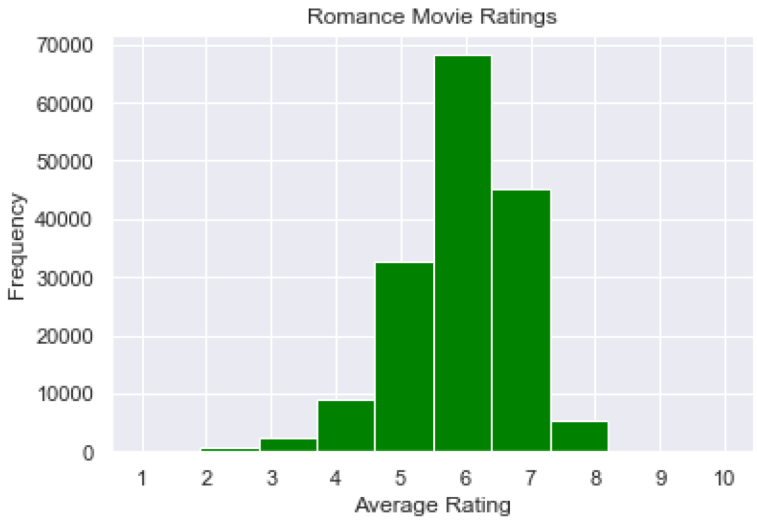


Set Up

- **Input:** $x \in \mathbb{R}^D$, D = {startYear, region, director, types}
- **Output:** $y \in \{0,1\}$

y = 1 if rating >= 6.5 "Recommended"

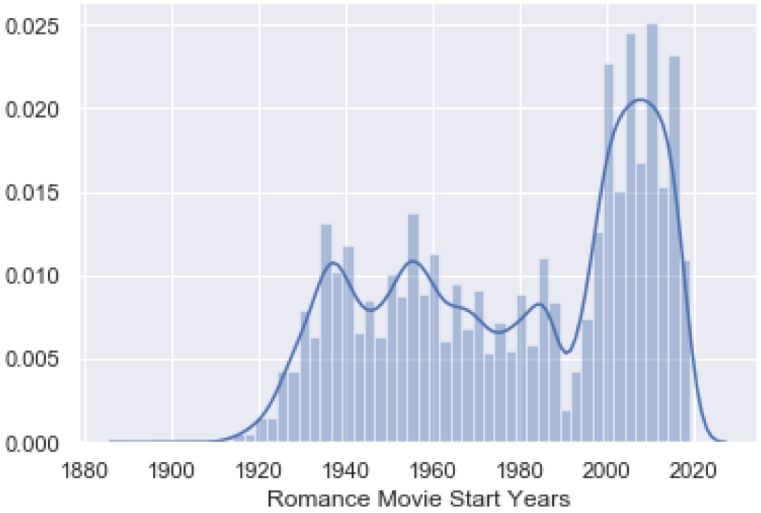
y = 0 if rating < 6.5 "Unrecommended"



Plotted using seaborn

Preprocess Data

- **Read** data from file
- Apply **clean**ing function
  - startYear: **center** the data at 1980
  - region: **eliminate** '\N'
  - types: `split(',')[0].strip()`
  - genre: only **preserve** 'Romance'
- Create a **mask**
- **Merge** features of interest into one table according to their IDs




```
# merge all data that we want to use into a single table called "movies"
movies = yearAndGenre[mask].merge(rating, on='tconst')
movies = movies.merge(regionAndType, on='tconst')
movies = movies.merge(directors, on='tconst')
```

Get Feature Matrix

- "Bag of words" model
- One-hot **encoding**
- **Concatenate** features
- Result:

  (n_samples * sum of feature dimensions) matrix

Vocabulary:
Man, woman, boy, girl, prince, princess, queen, king, monarch

	1	2	3	4	5	6	7	8	9
man	1	0	0	0	0	0	0	0	0
woman	0	1	0	0	0	0	0	0	0
boy	0	0	1	0	0	0	0	0	0
girl	0	0	0	1	0	0	0	0	0
prince	0	0	0	0	1	0	0	0	0
princess	0	0	0	0	0	1	0	0	0
queen	0	0	0	0	0	0	1	0	0
king	0	0	0	0	0	0	0	1	0
monarch	0	0	0	0	0	0	0	0	1

Each word gets a 1x9 vector representation

```
def extract_dictionary()
Out [1]: {"original": 0}
def extract_matrix()
Out [2]: (1,0,0,...,0)
```

Get Feature Matrix -> Get Label Array

- "Bag of words" model
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prince	0	0	0	0	1	0	0	0	0
princess	0	0	0	0	0	1	0	0	0
queen	0	0	0	0	0	0	1	0	0
king	0	0	0	0	0	0	0	1	0
monarch	0	0	0	0	0	0	0	0	1

Each word gets a 1x9 vector representation

Dimensionality Reduction

- Shape of feature matrix: (10000, 497)
- **Truncated Singular Value Decomposition**: need experiments!

$$A_{nxp} = U_{nxn}\, S_{nxp}\, V^{T}_{pxp}$$

$$\begin{bmatrix} \sigma_1 & & & & & \\ & \sigma_2 & & & & \\ & & \sigma_3 & & & \\ & & & \sigma_4 & & \\ & & & & \ddots & \\ & & & & & \sigma_r \end{bmatrix}$$

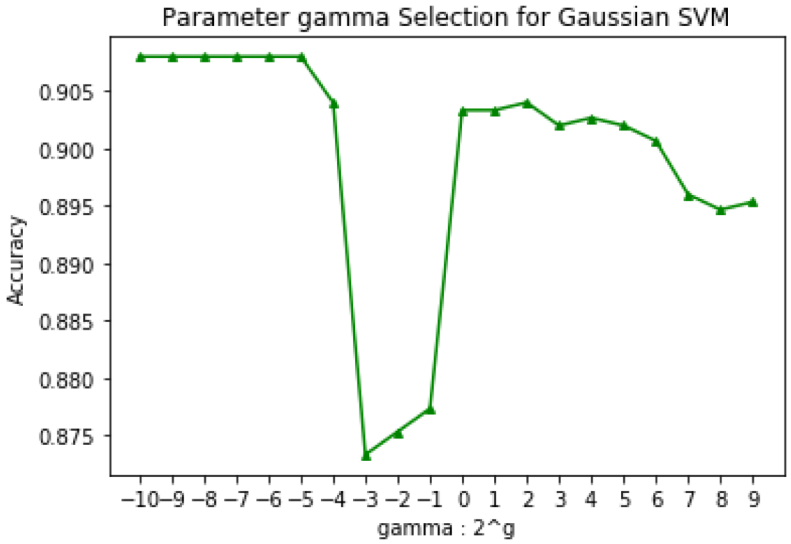
```
# apply singular value decomposition to reduce
# dimensionality for the input
tsvd = TruncatedSVD(n_components=100)
feature = tsvd.fit(feature).transform(feature)
```

Train Classifiers

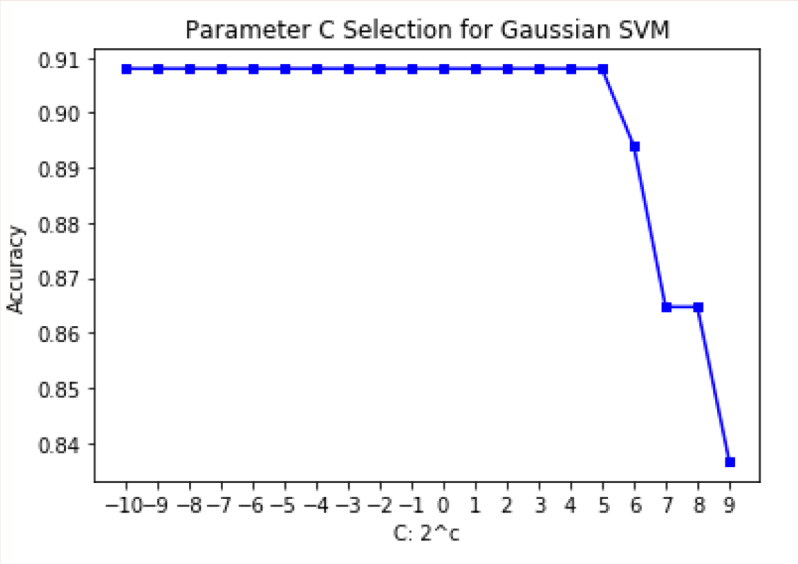
- Sample size: 10000, training size:8500

	Features	Accuracy
Dummy Classifier	uniform	0.5193
Gaussian SVM	**sklearn.StratifiedKFold sklearn.GridSearchCV**	**0.908**
Bernoulli Naïve Bayes		0.746
KNN	uniform weights/distance best k: 7 train score: 0.8267	0.8193

Best parameters for SVM: {'C': 1.0, 'gamma': 0.01}

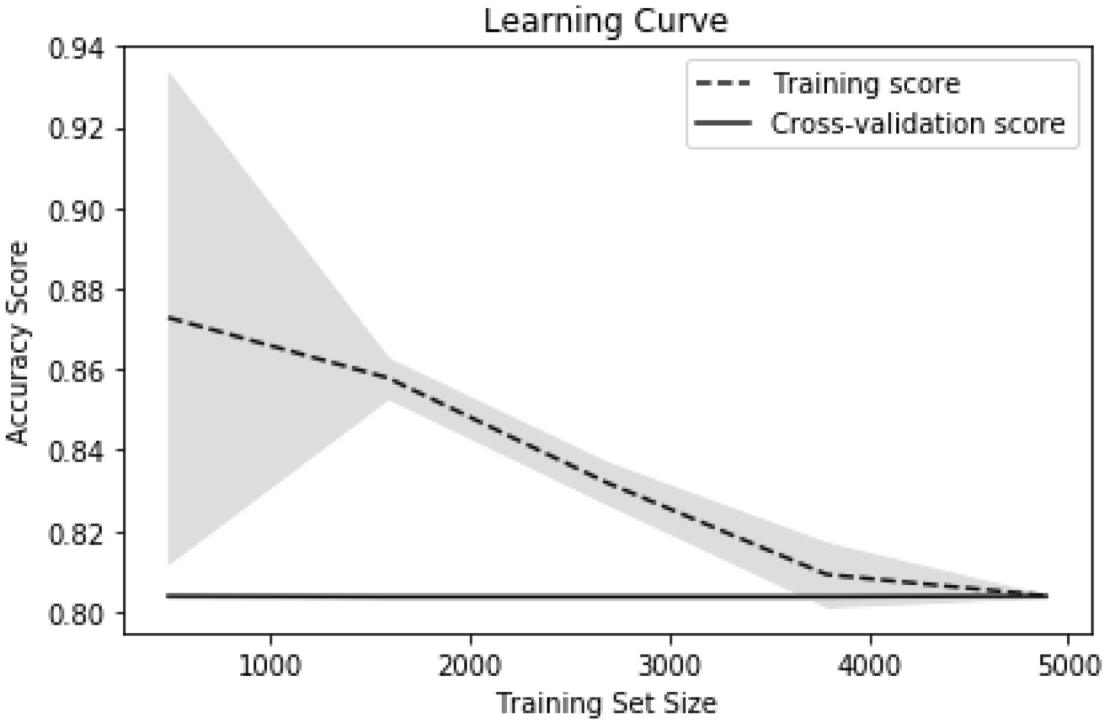


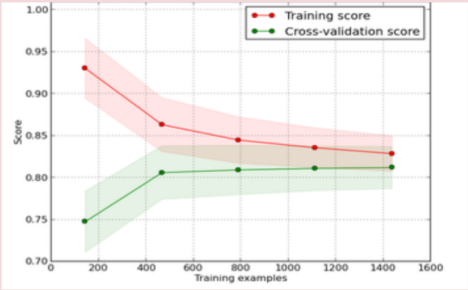
The γ parameter controls **how far the influence of a single training example can reach**. Low values mean that the influence can be far and high values mean close.



The C parameter balances between **correctly classifying** training instances and **maximizing** decision function's **margin**.

SVM Learning Curve





- Accuracy **decreases** as number of training sample increases
- Hard to **generalize**

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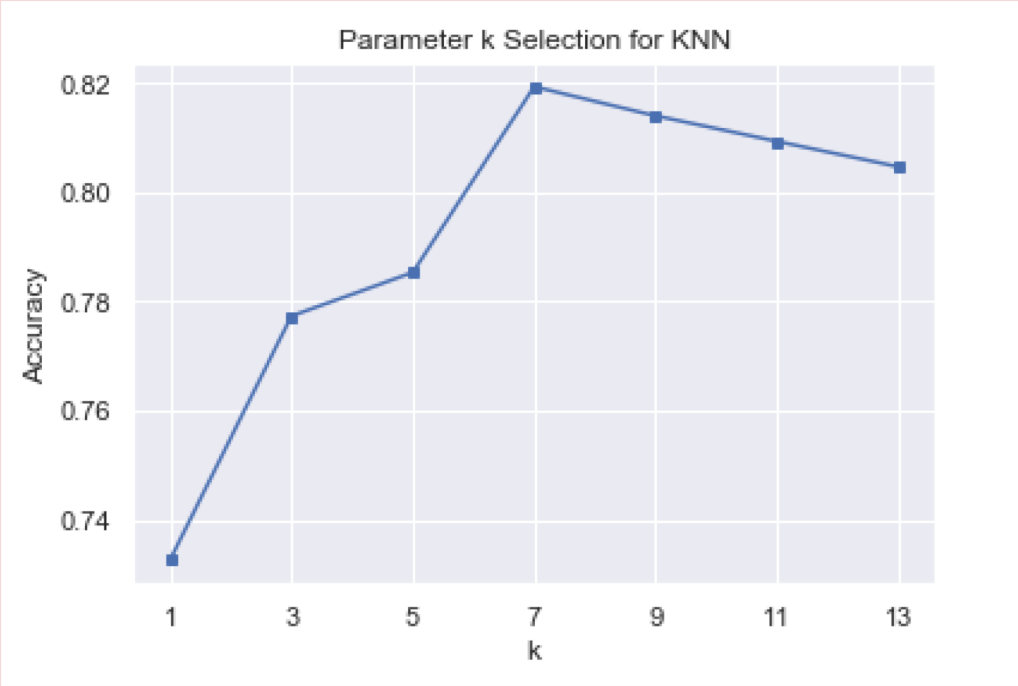
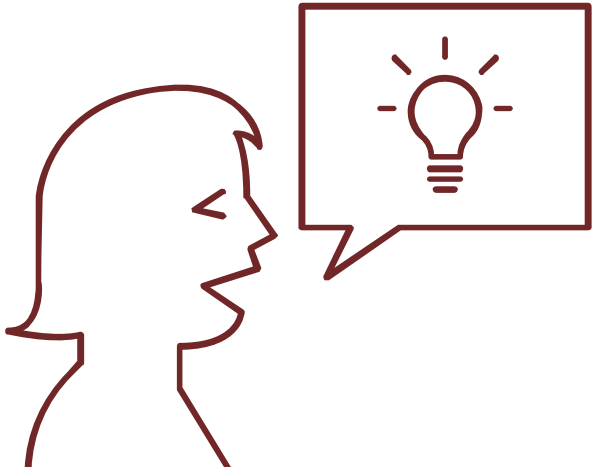
Best k for KNN:



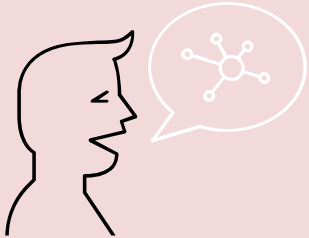


Interpretation

- **Features** are not absolutely deterministic, no strong relation
- **Models** are simple -> neural network
- Immature **data processing** -> apply further techniques in reducing noises
- **SVM** fits the best
- **Hyperparameters** are important

CONCLUSION

- As the film industry developed with time, romance movies experienced a fast development.
- Due to political, economical and cultural reasons, different countries understand romance differently and have distinct preferences.
- People have different standard/potential bias towards the quality of movies. It is hard to categorize a movie as good or bad.



Thanks for listening!